FORECASTING STOCK MARKET MOVEMENT DIRECTION USING SENTIMENT ANALYSIS AND SUPPORT VECTOR MACHINE

SK. MUBEENA[1], M. ANIL KUMAR[2], U. RAMYA[3], P. SUJATHA[4]

[1,2,3,4]*B. Tech Students, Dept of CSE, Tirumala Engineering College, Narasaropet, Guntur, A.P., India*

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Abstract - *Investor sentiment plays an important role on the stock market. User-generated textual content on the Internet provides a precious source to reflect investor psychology and predicts stock prices as a complement to stock market data. This paper integrates sentiment analysis into a machine learning method based on* ***SVM****. Furthermore, we take the day-of-week effect into consideration and construct more reliable and realistic sentiment indexes. Empirical results illustrate that the accuracy of forecasting the movement direction of the SSE 50 Index can be as high as 89.93% with a rise of 18.6% after introducing sentiment variables. And, meanwhile, our model helps investors make wiser decisions. These findings also imply that sentiment probably contains precious information about the asset fundamental values and can be regarded as one of the leading indicators of the stock market.*

Key Words: Support vector machine

1. INTRODUCTION:

FORECASTING stock market trends has been treated as one of the most challenging but important tasks. Stock market is a nonlinear and dynamic system, and investor sentiment constitutes key factor of the financial market[1]. With the proliferation of news, blogs, forums, and social networking websites, textual content on the Internet provides a precious source to reflect investor sentiment and predicts stock prices as a complement to traditional stock market time series data. Hence an automated approach is required to distill knowledge from alarge number of textual documents [2], [3]. Sentiment analysis is used to automatically extract views, attitudes, and emotions from the opinionated contents [4]. So, we employ sentiment analysis to construct sentiment indexes, and then aggregate them with stock market data to forecast movement direction.

1.1 RELATED WORK:

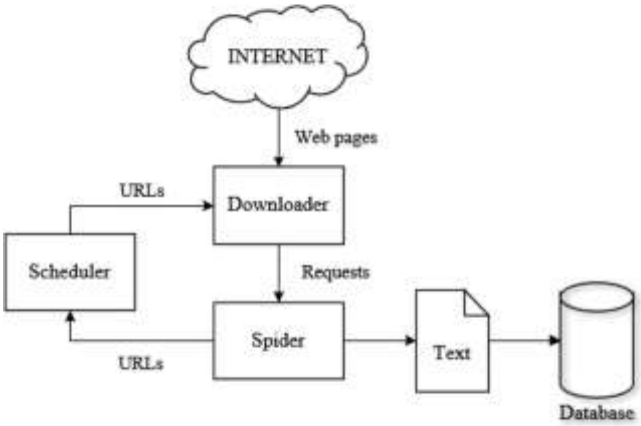
Sentiment Analysis in Finance Industry Sentiment is an opinion or feeling you have about something according to the Longman Dictionary. Sentiment analysis is the method to transfer unstructured textual contents to structured data, and distill views, attitudes, and emotions by language processing, data mining, and computational linguistics [11], [12]. Investor sentiment constitutes a key factor of the financial market [1]. Baker and Wurgler [13] employ the equity share in new issues, the dividend premium and some other variables as sentiment proxies, and point out that investor sentiment affects the cross section of stock returns. Edmans *et al.* [14] use international soccer results as a mood variable and document a significant market decline after each loss. Afterward, with the development of the sentiment analysis, researchers start to deal with written text that is a more direct way to express ideas and emotions. Tetlock [15] generates a pessimistic media factor in terms of the Wall Street Journal's "Abreast of the Market" column and finds that high pessimism has a negative effect on market prices followed by a subsequent reversion. Bollen *et al.* [16] present evidence that tweets posted on Twitter are a predictive factor of the Dow Jones Industrial Average (DJIA) values and find an accuracy of 86.7% in predicting the daily up and down changes in the closing values of the DJIA. Gillam *et al.* [17] concentrate on the volume of news to quantify the information incorporated in textual data and discover that it enhances earnings forecasting. Moreover, sentiment analysis is superior to the bag-of-words model at individual stock, sector, and index levels in predicting stock prices [12]. Oliveira *et al.* [18] propose an automated method to build a stock market sentiment lexicon to facilitate the research in the area. Nevertheless, the day-of-week effect is rarely mentioned in the study of investor sentiment.

1.2 SVM in Predicting Stock Market

SVM was proposed by Vapnik [19] and is a supervised learning method that can partially address the overfitting problem directly and formally [20]. With the help of kernel functions, such as radical basis function (RBF) kernel and polynomial kernel, it is able to solve the nonlinear problem by projecting it onto the high-dimensional feature space

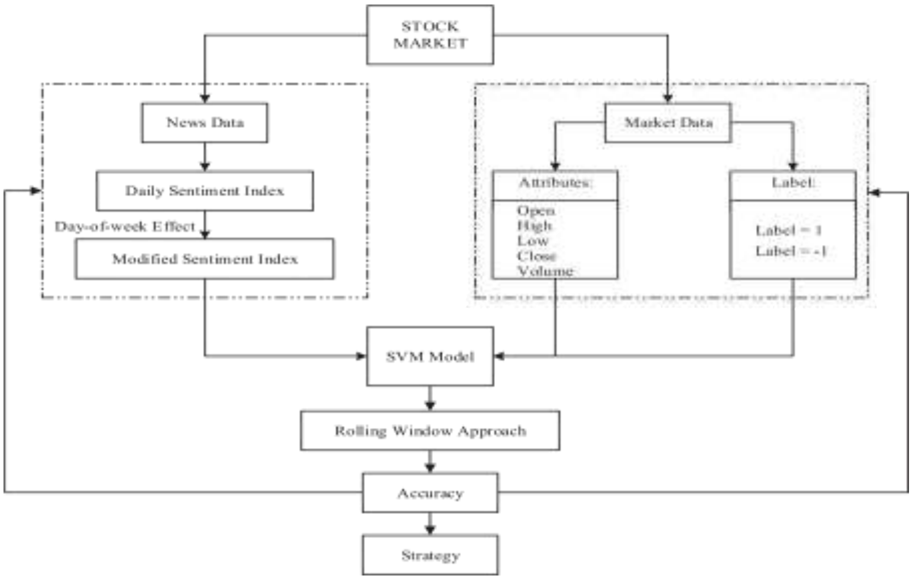
2. METHODOLOGY

This paper aims to forecast stock market movement direction by not only using financial market data, but also combining them with sentiment features that incorporate investor psychology. The features are extracted from unstructured news data automatically and then are expressed as sentiment indexes. In order to make the indexes more realistic and reliable, we take the day-of-week effect into consideration. Next, we employ SVM to forecast stock market trends, and make an adjustment to real market situations by use of a rolling window approach, and then compare the accuracy with the baseline method. Moreover, the prediction results are used to instruct investment decisions, and the performance of three different trading strategies are evaluated and compared. The overview of the stock market prediction architecture is illustrated in Fig. 1.



2.1. Investor Sentiment:

Step1 Web crawler In this step, we aim to build a web crawler to automatically download the targeted textual documents from the Internet and store them to a database for further processing. The framework is clarified in Fig. 2. The web crawler begins with the seeds in the form of a list of URLs. The scheduler manages the queue of URLs, deciding the priority and eliminating duplicate parts. Next, the downloader is responsible for acquiring the web pages from the Internet and providing them to the spider, which is used to parse the pages and extract the targeted contents. What we need to obtain is comprised of two sections: one is the textual news with the date from the websites, and



This section is made up of three steps. We first build a web crawler to download news documents automatically from the Internet, and then construct daily sentiment indexes based on

step 2: Sentiment calculation: we can compute 51 sentiment indexes for 51 stocks. In Step 2, we first segment each document into several sentences by identifying punctuations, such as "," "." and "!" Then sentences are divided into separate words, and if there appears a negative word, it is treated as a whole with the word next to it. For example, if people say "(I'm not satisfied with the stock)," after word segmentation, the sentence becomes four words "(I'm)" "(not)" "(satisfied with)" "(the)" "(stock)." If we directly project the words to the sentiment space, the program will tell us the sentence is optimistic because of the positive word "(satisfied with)." So, we need to treat "(not)" "(satisfied with)" as a whole "(not satisfied with)" so that we can find the true meaning. Then, we need to categorize each document, assume there are p_i positive sentences and n_i negative sentences in document i; if $p_i > n_i$, the document is positive; if $p_i = n_i$, the document is neutral; if $p_i < n_i$, the document is negative. And, then we find on the day t, the number of positive comments is M_t^{bull} and the number of negative comments is M_t^{bear}, so a daily sentiment index is calculated by using formula (1), with the value ranging from −1 to 1, where 0 means people hold a neutral position. And, if the value is between 0 and 1, it means people hold a positive view; if the value is between −1 and 0, it means people take a negative view. Then, by considering the day-of-week effec

Step 3 Modified sentiment: The day-of-week effect is one of the most well-known financial anomalies [5], which means that the average return on a Monday is much lower than that on the other days of the week. The reason includes that large amount of news is reported on the weekend or on Friday just after the market is closed. With such considerable and valuable information to deal with, investors are very likely to change their mind and take actions on Mondays. Furthermore, corporations also tend to release important news on the weekend to ensure the stability of the stock and boost the public image. If it is bad news, investors will have enough time to digest and accept it, whereas if it is good news, companies can continuously spread out news to make it known by more and more people and expand their coverage.

TABLE II DESCRIPTION OF EIGHT FEATURES

Features	Description
s1	The average of modified sentiment indexes
s2	The highest of modified sentiment indexes
s3	The lowest of modified sentiment indexes
s4	The median of modified sentiment indexes
s5	The value between the highest and the lowest
s6	The change of the average
s7	The percentage of the average change
s8	The standard deviation of modified sentiment indexes

sentiment indexes, the median of modified sentiment indexes, the average of modified sentiment indexes, the difference between the highest and the lowest, the change of the average (a certain day's average minus the last day's average), the percentage of the average change (a certain day's average minus the last day's average and divided by the last day's average), and the standard deviation of 51 modified sentiment indexes. Table II describes eight selected features. Fig. 3 sheds light on the trend of the 8 variables after standardization in 484 trading days.

2.2 Prediction:

First, we need to label the data according to the following equation:

$$\text{Label} = 1, \ \text{Close}_{t-}1 < \text{Close}_t \quad (16) \ -1, \ \text{Close}_t - 1 > \text{Close}_t$$

where Close_t denotes the close price of the SSE 50 Index, and Close_t-1 stands for the close price on the previous day. Besides, 1 also means buy order as it indicates the increase, whereas −1 means sell order as it implies the decline.

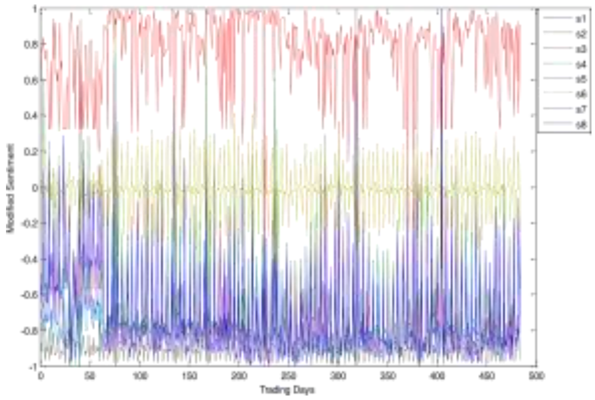
Next, we implement two experiments to predict the index movement direction. Experiment 1 is to use market data, which include opening price, closing price, high for the day, low for the day, trading volume in number of shares, trading volume in RMB, change in RMB, and change in percentage. And then, we combine them with sentiment features for Experiment 2. We employ classification accuracy Acc to assess the performance, as shown in the following equation:

$$\text{Acc} = \frac{T_{++} + T_{--}}{T_{++} + T_{--} + F_{-+} + F_{+-}} \quad (17)$$

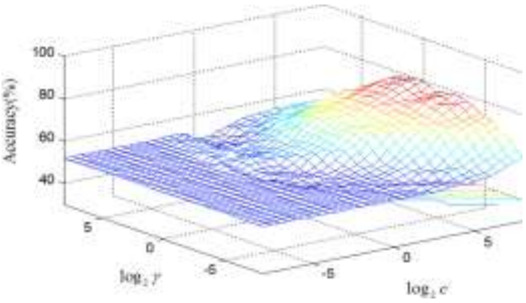
where T_{++} denotes that the true value is +1 and the prediction value is also +1; T−−denotes that the true value is −1 and the prediction value is also −1;F_{+}−denotes that the true value is +1, whereas the prediction value is −1;F−+ denotes that the true value is −1, whereas the prediction value is +1.

A fivefold cross-validation approach is adapted to train an SVM model. Eventually, we find the proper parameters and the kernel functions to achieve the best performance. Figs. 4 and 5 document the processes of parameter selection. Panel A of Table III sheds light on the prediction results. For Experiment 1, the accuracy can be 79.96%, and we use RBF kernel function, C = 256,γ = 0.9942; for Experiment 2, the accuracy can be as high as 97.73%, and we employ RBF kernel function, C = 181.0193,γ = 0.005524.

However, the two kinds of methods cannot be applied in forecasting stock market movement direction for the reason that they lead to look-ahead bias, which is created by the use of information or data that would not have been known or available during the period being analyzed. For example, we have some data from January to May, and implement the fivefold cross validation approach. When we use the data from February to May as training set and the data in January as testing set, it is impossible because in January, we will never know what will happen from February to May. On the other hand, that does not mean the method is useless, and it is an important procedure to select the proper kernel functions and parameters as well as address the overfitting problem. In other words, the purpose of the procedure is not to forecast but select the proper kernel functions and parameters.



3. Sentiment features in trading days:

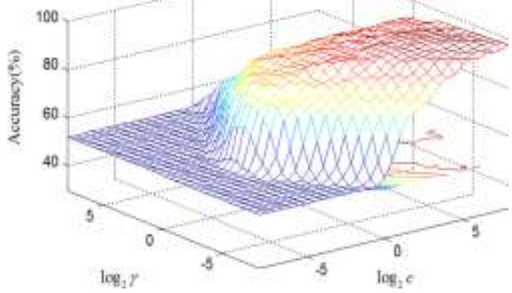


4. Investment Performance:

This section tries to discover if the prediction results are of benefit to the investment. Some measures are employed to evaluate and compare the performance of the methods. AI is computed based on the stock points. For example, if we buy a stock at the price of 100 and sell it at 150, then we earn 50 stock points and AI is 50 stock points; after that, we short the equity at 150 and liquidate the position at 120, then we make 30 stock points and AI becomes 80 stock points. Maximum drawdown (MDD) is the maximum decline of a series from a peak to a trough over a specified time period [26]. MDD at time T is expressed as

MDD = sup(18) $\left[\sup_{s\in[0,t]} X(s) - X(t)\right]$

$t \in [0,T]$



5. CONCLUSION AND FUTURE WORK

In this paper, we aim to exploit investor sentiment to forecast stock market movement direction by emphasizing the role of investors. Investor psychology drives the stock market [1] and it matters for our research. Accordingly, user-generated content on the Internet provides a precious source to reflect investor psychology. Sentiment analysis is used to convert unstructured textual documents into daily sentiment indexes. Furthermore, the financial anomaly day-of-week effect that means the average return on Mondays is much lower than that on the other days of the week probably influences the precision of the sentiment indexes, so we adjust the indexes by introducing an exponential function on past sentiment changes on weekends and then generalize to holidays. Correspondingly, Sina Finance and Eastmoney, two typical financial websites, were selected as experimental platforms to obtain a corpus of financial review data. Then, the machine learning model SVM is employed to predict a very important index in China, the SSE 50 Index, by implementing fivefold cross validation and a realistic rolling window approach. Empirical results illustrate that combining sentiment features with stock market data can achieve a much better performance than just using stock

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